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AI in Adjudication and Administration

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Abstract

The use of artificial intelligence has expanded rapidly in recent years across many aspects of the economy. For federal, state, and local governments in the United States, interest in artificial intelligence has manifested in the use of a series of digital tools, including the occasional deployment of machine learning, to aid in the performance of a variety of governmental functions. In this Article, we canvass the current uses of such digital tools and machine-learning technologies by the judiciary and administrative agencies in the United States. Although we have yet to see fully automated decision-making find its way into either adjudication or administration, governmental entities at all levels are taking steps that could lead to the implementation of automated, machine-learning decision tools in the relatively near future. Within the federal and state court systems, for example, machine-learning tools have yet to be deployed, but other efforts have put in place digital building blocks toward such use. These efforts include the increased digitization of court records that algorithms will need to draw upon for data, the growth of online dispute resolution inside and outside of the courts, and the incorporation of non-learning risk assessment tools as inputs into bail, sentencing, and parole decisions. Administrative agencies have proven much more willing than courts to use machine-learning algorithms, deploying such algorithmic tools to help in the delivery of public services, management of government programs, and targeting of enforcement resources. We discuss already emerging concerns about the deployment of artificial intelligence and related digital tools to support judicial and administrative decision-making. If artificial intelligence is managed responsibly to address such concerns, the use of algorithmic tools by governmental entities throughout the United States would appear to show much future promise. This Article's canvass of current uses of algorithmic tools can serve as a benchmark against which to gauge future growth in the use of artificial intelligence in the public sector.

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Cary Coglianese[*] & Lavi M. Ben Dor[**]

Artificial intelligence has begun to permeate many aspects of U.S. society.[1] In settings as varied as medicine, transportation, financial services, and entertainment, digital technologies continue to emerge that rely on machine-learning algorithms to process vast quantities of data and make highly accurate predictions that can often outperform human ability to perform similar tasks.[2] As a result, the potential utility of artificial intelligence in the legal field has not gone unnoticed, with scholars, attorneys, and judges beginning to examine the implications it could have for the United States legal system.[3]

This Article seeks to capture the state of the art of the current uses of digitization, algorithmic tools, and machine learning in domestic governance in the United States. It serves, in effect, as a status report on non-military governmental use—that is, functions by courts and administrative agencies—of artificial

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[1] While a variety of definitions for the term "artificial intelligence" exist, a helpful one is "[t]he theory and development of computer systems able to perform tasks normally requiring human intelligence." *Artificial Intelligence*, OXFORD DICTIONARIES, https://en.oxforddictionaries.com /definition/us/artificial-intelligence (last visited Nov. 20, 2019). The terms "machine learning" and "artificial intelligence" are to some extent interchangeable and are used as such throughout this Article. *Cf.* Cary Coglianese & David Lehr, *Transparency and Algorithmic Governance*, 71 ADMIN. L. REV. 1, 2 n.2 (2019) ("By "artificial intelligence" and "machine learning," we refer . . . to a broad approach to predictive analytics captured under various umbrella terms . . . . For our purposes, we need not parse differences in the meaning of these terms, nor will we delve deeply into specific techniques within machine learning.").

[2] *See, e.g.*, Cary Coglianese, *Using Machine Learning to Improve the U.S. Government*, REG. REV. (Aug. 12, 2019), https://www.theregreview.org/2019/08/12/coglianese-using-machine-learning-to-improve-us-government/; Peter Dizikes, *AI, the Law, and Our Future*, MIT NEWS OFFICE (Jan. 18, 2019), http://news.mit.edu/2019/first-ai-policy-congress-0118; Jillian D'Onfro, *AI 50: America's Most Promising Artificial Intelligence Companies*, FORBES (Sept. 17, 2019), https://www.forbes.com/sites/jilliandonfro/2019/09/17/ai-50-americas-most-promising-artificial-intelligence-companies/#54bfb84c565c; Chris Weller, *A California Police Department is Using Software to Decide if You're About to Commit a Crime*, BUS. INSIDER (Jan. 12, 2016), https://www.businessinsider.com/intrado-beware-system-tracks-threat-levels-2016-1 ("A new piece of software in place at the Fresno Police Department in central California uses huge batches of data, ranging from criminal history to Twitter feeds, to assess how likely someone is to commit a crime and whether the police ought to keep tabs on them.").

[3] *See, e.g.*, Daniel L. Chen, *Machine Learning and the Rule of Law* 4-7 (Working Paper, 2019), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3302507 (noting that machine learning may be useful in detecting and adjusting for bias in judicial decision-making on asylum requests).

intelligence and its building blocks throughout the United States.[4] With responsibility for domestic governance is divided in a federalist structure across fifty-one governments—those of the fifty states plus the national government—the scope of our coverage is vast.[5] Its subject matter is also a rapidly changing one. As new technologies and applications emerge in the private sector, both pressures and opportunities for their use in public sector settings will grow. The vast scope and fast pace of algorithmic governance makes the kind of stock-taking reflected in this paper all the more valuable for informing both scholarship and public deliberation. To assess the value artificial intelligence holds as well as identify opportunities for its application in domestic governance, it is essential to understand where and how it is currently being used. Such a stock-taking can also facilitate future research evaluating current applications and making recommendations for the diffusion of artificial intelligence in new settings.

Such stock-taking is also valuable because there currently exists no centralized repository of applications of artificial intelligence by courts and administrative agencies.[6] Given the U.S. federalist structure, the development and implementation of this technology is also not determined in any central institution. Technology decisions are made at the federal level in as many as several hundreds of separate administrative agencies.[7] The number of comparable agencies at the state and local level surely runs into the tens of thousands, and apparently no one has ever tried to count them all. Even with respect simply to law enforcement agencies, it has been noted that "the decentralized, fragmented, and local nature of law enforcement in the United States makes it challenging to accurately count the number of agencies."[8] But, in 2008, approximately 18,000 different police

[4] Military and security intelligence-gathering uses would obviously be subject to security classification. For the most in-depth treatment of artificial intelligence in U.S. military applications, see generally PAUL SCHARRE, ARMY OF NONE: AUTONOMOUS WEAPONS AND THE FUTURE OF WAR (2018).

[5] *See generally, e.g.*, Robert A. Schapiro, *Toward a Theory of Interactive Federalism,* 91 IOWA L. REV. 243 (2005); Philip J. Weiser, *Federal Common Law, Cooperative Federalism, and the Enforcement of the Telecom Act,* 76 N.Y.U. L. REV. 1692 (2001).

[6] One effort to provide such a repository can be found on the Penn Program on Regulation's website on "Optimizing Government." *Uses in Government*, PENN LAW: OPTIMIZING GOVERNMENT, https://www.law.upenn.edu/institutes/ppr/optimizing-government-project/government.php#municipal (last visited Feb. 6, 2020). Another such project, which documents several dozen uses by local and state government agencies, is the Data-Smart City Solutions initiative run by Harvard University. *A Catalog of Civic Data Use Cases*, HARVARD KENNEDY SCHOOL: DATA-SMART CITY SOLUTIONS (Oct. 9, 2019), https://datasmart.ash.harvard.edu/news/article/how-can-data-and-analytics-be-used-to-enhance-city-operations-723.

[7] Indeed, just getting a count of the number of federal agencies is difficult. One scholarly report published by a governmental agency noted that "there is no authoritative list of government agencies. Every list of federal agencies in government publications is different." DAVID E. LEWIS & JENNIFER L. SELIN, SOURCEBOOK OF UNITED STATES EXECUTIVE AGENCIES (2012), https://www.acus.gov/sites/default/files/documents/Sourcebook-2012-Final_12-Dec_Online.pdf (reporting estimates of the number of federal administrative agencies that range from 252 to 405).

[8] U.S. DEP'T OF JUSTICE, NATIONAL SOURCES OF LAW ENFORCEMENT EMPLOYMENT DATA 1 (Oct. 4, 2016), https://www.bjs.gov/content/pub/pdf/nsleed.pdf.

departments and other law enforcement agencies responded to a federally sponsored Census of State and Local Law Enforcement Agencies.[9]

Similar numbers describe the judiciary in the United States. The federal court system comprises, in addition to one Supreme Court, a total of thirteen "circuits" in the federal appellate court system and ninety-four trial court "districts" (each with dozens of trial judges that in total number over 650 courtrooms).[10] At the state level, the number of different courts proliferates still further—especially given that state governments further delegate domestic authority to county and municipal governments. According to the National Center for State Courts, approximately 15,000-17,000 different state and municipal courts exist in the United States.[11]

Any one of these numerous judicial or administrative entities could in principle have its own policy with respect to electronic filing, digitization of documents, or the use of algorithms to support decision-making.[12] As a result, it is valuable for decision-makers in any of these settings, as well as scholars and practitioners, to have a source to turn to that catalogs current uses of artificial intelligence and its building blocks across the United States. Of course, any such survey of uses must be made with appropriate caution, as we can make no claim to have identified every use by any governmental entity. This Article is based primarily on extensive searches of academic literature and media publications in an effort to identify current uses of machine-learning algorithms in decision support systems used by state and federal courts and agencies. We also spoke with court and agency officials who would be in a position to know about the current uses of artificial intelligence and its building blocks by governmental entities, as well as leading consultants and academic experts developing and studying such possible uses. This research effort generated as comprehensive a survey of judicial and administrative uses of machine learning across federal and state governments as any of which we know.

The results of our research lead us to be quite confident in two overarching conclusions. First, no judicial or administrative body in the United States has instituted a system that provides for total decision-making by algorithm, such that a digital system makes a fully independent determination (that is, a human "out of the loop" decision).[13] Second, we are also aware of no *court* that is currently relying

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[9] *Id*. at 6.

[10] *See, e.g., Court Role and Structure*, U.S. COURTS, https://www.uscourts.gov/about-federal-courts/court-role-and-structure (last visited Nov. 20, 2019).

[11] This estimate is based on a telephone and email exchange with NCSC staff, and it includes a vast number of municipal courts. Indeed, the uncertainty reflected in the range (rather than a point estimate) is apparently due to fairly regular changes in the size and organization of municipal courts.

[12] *See, e.g.,* U.S. SUPREME COURT, RULES OF THE SUPREME COURT (adopted Sept. 27, 2017), https://www.supremecourt.gov/filingandrules/2017RulesoftheCourt.pdf; FED. R. CIV. P. 83(a) ("[A] district court, acting by a majority of its district judges, may adopt and amend rules governing its practice."); FED. R. APP. P. 47(a)(1) ("Each court of appeals acting by a majority of its judges in regular active service may . . . make and amend rules governing its practice.").

[13] For a discussion of the difference between using algorithms on a supportive versus determinative basis, see Coglianese & Lehr, *supra* note 1, at 31; Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147, 1167-1170 (2017).

in any way, even on a human-in-the-loop basis, on machine-learning algorithms for *judicial* decisions. That said, one state has a parole board using a system based on a machine-learning algorithm to support prisoner release decisions, and numerous federal and state agencies have deployed or are currently researching the use of machine learning in support of various *administrative* functions.

Here, we distinguish such machine-learning algorithms—which we treat here as defining artificial intelligence— from two building blocks that might help lead to the eventual governmental use of artificial intelligence: digitization and algorithmic tools. Indeed, machine learning resides on the far end of a spectrum of digital technologies available to governments. The closest point on that spectrum begins with simple *digitization*—or the use of electronic filing or other data systems to manage information in electronic format. Digitization is a building block toward artificial intelligence because it can facilitate the availability of the "Big Data" on which machine learning is based. Next on the spectrum would be for governments to rely on what we call here *algorithmic tools*—that is, traditional, human-created statistical models, indices, or scoring systems that are then used as decision tools. These traditional algorithmic or statistical tools rely on humans to select the specific variables to be included in a decision aid and the precise mathematical relationships between those variables. Only the final step on the spectrum—*machine learning*—constitutes what we will consider artificial intelligence, because learning algorithms essentially work "on their own" to process data and discover optimal mathematical relationships between them. This autonomous self-discovery is what gives machine-learning algorithms not only their name but also their frequent superior performance in terms of accuracy over traditional algorithmic tools. Of course, even with machine learning, humans must specify the objective that the learning algorithm is supposed to forecast or optimize, and humans must undertake a number of steps to "train" the algorithm and refine its operation.[14] Yet these learning algorithms are different than traditional statistical tools because the precise ways that data are combined and analyzed are neither determined in advance by a human analyst nor easily explainable after the fact. For this reason, machine-learning algorithms are often described as "black-box" algorithms because they do not afford a ready way of characterizing how they work—other than that they can be quite accurate in achieving the objectives they have been designed to achieve.

In the rest of this Article, we first take up the status of artificial intelligence in the federal and state judiciaries. More precisely, we report on three building blocks that might eventually lead to the use of artificial intelligence in the courts: the increased digitization of court records, the use of algorithmic tools for risk assessment in aspects of the criminal justice process, and the growth of online dispute resolution outside of the courts. The most widespread innovation in the courts has occurred in various forms of digitization (such as electronic filing and case management), while some courts have relied on algorithmic tools to support pretrial, sentencing. or parole decisions. Some courts also recognize a role for online dispute resolution systems developed by the private sector.

[14] For an excellent primer on machine learning, see David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653, 669 (2017).

We turn in Part II to a review of administrative agencies' use of artificial intelligence. Many administrative systems have been digitized for some time, and administrative agencies have also long relied on traditional statistical analysis or algorithmic tools. But most relevant to the purposes of this Article, some administrative agencies at the local, state, and federal level are also starting to use machine learning for certain analytical and decision support purposes. We thus devote our attention in Part II to these latter uses of machine learning in the administrative context.

In both Parts of this Article, we also highlight some of the legal issues, and at times the litigation and public controversy, that has surrounded certain applications of algorithmic tools or machine learning. Given the increased use of artificial intelligence in other facets of society, as well as in many other parts of the world, the path toward greater governmental reliance on machine learning in the United States will likely continue to move forward. At some point in the not-too-distant future, autonomous decision-making systems based on machine learning may well begin to take the place of a government singularly and literally "of the people" and "by the people" in the United States.[15]

I. ARTIFICIAL INTELLIGENCE BUILDING BLOCKS IN THE COURTS

As of today, of course, we know of no machine-learning tool that has been adopted in any court in the United States to make an ultimate, fully automated determination on a legal or factual question.[16] However, several trends in recent years have emerged that could signal movement towards the eventual use of such automated adjudication via artificial intelligence. To date, the principal building blocks of artificial intelligence in the courts comprise the digitization of court filings and processes, the introduction of algorithmic tools for certain criminal court decisions, and the emergence of online dispute resolution as an alternative to traditional court proceedings for small claims.

A. *Digitization of Court Records*

Artificial intelligence depends on data.[17] Increasingly, court systems in the United States have made data more easily accessible through the growing

[15] Abraham Lincoln, Address Delivered at the Dedication of the Cemetery of Gettysburg (Nov. 19, 1863).

[16] *See* Richard C. Kraus, *Artificial Intelligence Invades Appellate Practice: The Here, The Near, and The Oh My Dear*, AM. BAR ASS'N (Feb. 5, 2019), https://www.americanbar.org/groups/judicial/publications/appellate_issues/2019/winter/artificial-intelligence-invades-appellate-practice-the-here-the-near-and-the-oh-my-dear/ (noting that in the United States, "the more fantastic ideas such as using AI to objectively decide cases by analyzing facts and applying law . . . are still figments of creative imaginations").

[17] *See Willem Sundblad*, *Data Is the Foundation for Artificial Intelligence and Machine Learning*, FORBES (Oct. 18, 2018), https://www.forbes.com/sites/willemsundbladeurope/2018/10/18/data-is-the-foundation-for-artificial-intelligence-and-machine-learning/#4bd8c64051b4 ("[D]ata is both the most underutilized asset of manufacturers and the foundational element that makes AI so powerful.").

digitization of court documents.[18] This digitization has in large part been internally driven by the courts. Courts at both the state and federal level, including the Supreme Court itself, have required electronic filing as one of several ways a party can submit motions or arguments to a court, or as the only method of doing so.[19] In addition, virtually every state and the federal government post free forms online that can be downloaded and used by litigants.[20] Some courts have created "dedicated computer kiosks" specifically designed to help litigants who lack legal representation.[21] In California, for example, an "'Online Self-Help Center' offers PDFs that can be filled in online and used for evictions, divorces, orders of protection, collection matters, small claims, and other issues."[22]

The federal judiciary has instituted a "comprehensive case management system" known as the Case Management/Electronic Case Files (CM/ECF) system that allows for convenient filing and organization of court documents, party pleadings, and other relevant materials.[23] In 2002, Congress directed the federal courts to ensure that, with exceptions for certain documents filed under seal, "any document that is filed electronically [is also] publicly available online."[24] State and local courts have increasingly rolled out various electronic filing (or "e-filing")

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[18] *See, e.g.*, Jenni Bergal, *Courts Plunge into the Digital Age*, PEW CHARITABLE TRUSTS: STATELINE (Dec. 8, 2014), https://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2014/12/8/courts-plunge-into-the-digital-age (noting that the status of courthouses' digital use "has been changing dramatically in many courthouses across the country. States are moving to systems in which documents are submitted electronically, file rooms are disappearing and the judicial system is going paperless"); *Records/Document Management Resource Guide*, NAT'L CTR. FOR STATE COURTS, https://www.ncsc.org/Topics/Technology/ Records-Document-Management/Resource-Guide.aspx (last updated Sept. 26, 2018) ("Records and document management are at the core of most courts' business processes. . . . [M]any state courts have implemented electronic court records (ECR) and electronic data management systems (EDMS) in an effort to improve court operations and manage unruly paperwork.").

[19] *See, e.g.*, SUP. CT. R. 29 (requiring that in addition to filing documents with the Court Clerk, "all filers who are represented by counsel must submit documents to the [Supreme] Court's electronic filing system"); 7TH CIR. R. 25 ("All documents must be filed and served electronically."); E.D. PA. LOCAL R. 5.1.2 ("All civil and criminal cases filed in this court are required to be entered into the court's Electronic Case Filing ("ECF") System . . . ."); CA R. CT. 2.253 (empowering state courts in California to either permit or require parties to file electronically).

[20] *Self Representation*, NAT'L CTR. FOR STATE COURTS, https://www.ncsc.org/Topics/Access-and-Fairness/Self-Representation/State-Links.aspx?cat=Court%20Forms (last visited Nov. 20, 2019).

[21] BENJAMIN H. BARTON & STEPHANOS BIBAS, REBOOTING JUSTICE 123 (2017).

[22] *Id.* at 119. Barton and Bibas report that in a single year more than 4 million people visited the California self-help portal. They also report successful experiences with other systems for "DIY" lawyering, such as a system in New York State. *Id.* at 119-123.

[23] *Case Management/Electronic Case Files*, PACER, https://www.pacer.gov/cmecf/. Public access to PACER data is not free, which has generated some controversy. *See, e.g.*, David Post, *Yes, PACER Stinks . . . But Is It Also Overcharging Its Customers?*, WASH. POST (Jan. 9, 2016), https://www.washingtonpost.com/news/volokh-conspiracy/wp/2016/01/09/yes-pacer-stinks-but-is-it-also-overcharging-its-customers/?utm_term=.49cf19383d86. Similar concerns have been expressed related to the video recording of judicial proceedings. *See, e.g.*, Jonathan Sherman, *End the Supreme Court's Ban on Cameras*, N.Y. TIMES (Apr. 24, 2015), https://www.nytimes.com/2015/04/24/opinion/open-the-supreme-court-to-cameras.html.

[24] E-Government Act of 2002, 107 Pub. L. No. 347, § 205(c)(1), 116 Stat. 2899, 2914.

software to replace paper submissions and docketing, many in the past decade.[25] In Florida alone, individuals filed roughly 23.5 million documents totaling about 110 million pages from mid-2018 to mid-2019.[26] These systems have created massive repositories of filings from litigants and judicial decisions and orders, all held in centralized databases.

In principle, artificial intelligence could take advantage of all of this data. At law firms, the increasing use of algorithmic tools, including those involving machine-learning algorithms, can be found to support the review of documents during the discovery process. This "e-discovery" practice has been shown to have a "strong impact" on reducing the need for human labor—plus it has spawned services that seek to analyze trends and make legal forecasts.[27] In addition, artificial intelligence has been used by outside researchers to attempt to predict courts' decisions using data. In a 2017 study, a machine-learning statistical model correctly predicted the outcome of 70% of 28,000 U.S. Supreme Court decisions and 72% of individual justices' votes from 1816 to 2015.[28] With a growing amount of data available from courts at all levels across the country, it is likely that such predictive efforts will only improve in quality in the future. In time, it may also be possible that artificial intelligence tools will have gained enough "experience" in document review to step into the role of the judges and, rather than just predicting their behavior, use the large troves of data available in electronic filing systems to help in making actual judicial determinations.

B. *Risk Assessment Algorithms*

Algorithmic tools have taken root in some court systems as an aid to judicial decision-making in criminal cases on questions of bail, sentencing, and parole—but so far virtually none of these appear to rely on *machine-learning* algorithms.

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[25] *Electronic Filing,* NAT'L CTR. FOR STATE COURTS, https://www.ncsc.org/Topics/Technology/Electronic-Filing/State-Links.aspx (last visited Nov. 20, 2019). For examples of state court "e-filing" systems, see *eCourts*, N.J. COURTS, https://njcourts.gov/attorneys/ecourts.html (last visited Nov. 20, 2019); *Electronic Filing in the Delaware Judiciary*, DEL. COURTS, https://courts.delaware.gov/efiling/ (last visited Nov. 20, 2019); *Active Courts*, ODYSSEY EFILEGA, http://www.odysseyefilega.com/active-courts.htm (last visited Nov. 20, 2019); EFILETEXAS, https://www.efiletexas.gov/ (last visited Nov. 20, 2019); *Superior Court Electronic Case Filing*, N.H. JUDICIAL BRANCH, https://www.courts.state.nh.us/nh-e-court-project/superior-attorneys.htm (last visited Nov. 20, 2019) (noting that e-filing in the New Hampshire Superior Court became mandatory in September 2018).

[26] *2018-2019 Annual Statistics*, FL. COURTS E-FILING PORTAL (June 25, 2019), http://archive.flclerks.com/e-Filing_Authority/Resources/2018-2019_Board_Meetings/June_25_2019_Board_Meeting/Annual_Statistics_2018-2019May.pdf.

[27] *See, e.g.,* Dana Remus & Frank Levy, *Can Robots Be Lawyers: Computers, Lawyers, and the Practice of Law*, 30 GEO. J. LEGAL ETHICS 501, 515-16 (2017). Various private sector efforts are underway to make use of court data for predictive analytic purposes. One major service is Lex Machina, https://lexmachina.com/, which is used by law firms. Another service, Docket Navigator, http://brochure.docketnavigator.com/, performs some basic analytics (albeit not with machine learning) for intellectual property cases.

[28] *See* Matthew Hutson, *Artificial Intelligence Prevails at Predicting Supreme Court Decisions*, SCIENCE (May 2, 2017), https://www.sciencemag.org/news/2017/05/artificial-intelligence-prevails-predicting-supreme-court-decisions.

An algorithmic tool for bail decisions before trial that had originally been developed by the Arnold Foundation has been adopted by at least four states (Arizona, Kentucky, New Jersey, and Utah) and about a dozen municipal courts, largely in major metropolitan areas.[29] According to a recent report by two media justice advocacy organizations, all but four states have apparently adopted some kind of risk assessment tool in sentencing decisions.[30] More than half of the states use some form of algorithmic tool for purposes of parole decision-making.[31] The federal government has recently announced an algorithmic tool for parole decisions: Prisoner Assessment Tool Targeting Estimated Risk and Needs (PATTERN).[32] The PATTERN system was developed in response to federal legislation calling for the use of risk assessment in federal parole decisions. Similarly, some state statutes encourage or require the use of these algorithmic tools,[33] while others are selected at the discretion of state or local officials.[34]

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[29] *See* ARNOLD VENTURES, PUBLIC SAFETY ASSESSMENT FAQS ("PSA 101") (Mar. 18, 2019), https://craftmediabucket.s3.amazonaws.com/uploads/Public-Safety-Assessment-101_190319_140124.pdf.

[30] *National Landscape*, MAPPING PRETRIAL INJUSTICE, https://pretrialrisk.com/national-landscape/ (last visited Feb. 10, 2020). Just six years ago, it was reported that only twenty states used such tools. *See* Sonja Starr, *Evidence-Based Sentencing and the Scientific Rationalization of Discrimination*, 66 STAN. L. REV. 803, 809 (2014). Federal courts, meanwhile, must consider the Sentencing Guidelines, which set out suggested sentence ranges for federal offenses depending on a variety of factors—a somewhat crude, if older and non-digital style of algorithm. *See* U.S. SENTENCING GUIDELINES MANUAL (U.S. SENTENCING COMM'N 2018); *see also Kimbrough v. United States*, 552 U.S. 85, 108-09 (2007) (noting that the Sentencing Guidelines are advisory but nonetheless should play a "key role" in judges' considerations).

[31] BERNARD E. HARCOURT, AGAINST PREDICTION: PROFILING, POLICING, AND PUNISHING IN AN ACTUARIAL AGE 77 (2007) (noting twenty-eight states were using an algorithmic risk assessment tool for parole decision-making as of 2004).

[32] U.S. DEPARTMENT OF JUSTICE, THE FIRST STEP ACT OF 2018: RISK AND NEEDS ASSESSMENT SYSTEM (2019), https://nij.ojp.gov/sites/g/files/xyckuh171/files/media/document/the-first-step-act-of-2018-risk-and-needs-assessment-system_1.pdf; *see also* Brandon Garrett & John Monahan, *Assessing Risk: The Use of Risk Assessment in Sentencing*, JUDICATURE, Summer 2019, https://judicature.duke.edu/articles/assessing-risk-the-use-of-risk-assessment-in-sentencing/ (noting that the FIRST STEP Act "mentions risk no less than 100 times and relies on risk assessments to allocate prison programming and prisoner release").

[33] *See, e.g.*, ALA. STAT. § 12-25-33(6) (2019) (instructing the Alabama Sentencing Commission to develop a risk assessment instrument to be "predictive of the relative risk that a felon will become a threat to public safety"); KY. REV. STAT. ANN. § 532.007(3)(a) (2019) ("Sentencing judges shall consider . . . the results of a defendant's risk and needs assessment included in the presentence investigation . . . ."); OHIO REV. CODE ANN. § 5120.114(A) (2019) (allowing for the use of a risk assessment tool by a variety of adjudicatory bodies in the criminal justice system); OKLA. STAT. tit. 22, § 988.18 (2019) (requiring courts to use a risk assessment tool in determining an offender's eligibility for a sentence of community service); 42 PA. CONS. STAT. § 2154.7 (2019) (requiring the Pennsylvania Commission on Sentencing to adopt a risk assessment tool to "be used as an aide in evaluating the relative risk that an offender will reoffend and be a threat to public safety"); W. VA. CODE § 62-12-6(a)(2) (2019); *see also* ARIZ. CODE OF JUDICIAL ADMIN. § 6-201.01(J)(3) (2016) ("For all probation eligible cases, presentence reports shall [] contain case information related to criminogenic risk and needs as documented by the standardized risk assessment and other file and collateral information.").

[34] *See, e.g.*, BD. OF DIRS. OF THE JUDICIAL CONFERENCE OF IND., POLICY FOR INDIANA RISK ASSESSMENT SYSTEM (Apr. 23, 2010), https://www.in.gov/judiciary/cadp/files/prob-risk-iras-2012.pdf (last updated Sept. 14, 2012); R.I. DEP'T OF CORRS., LEVEL OF SERVICE INVENTORY-

As best we can determine, only one jurisdiction (Pennsylvania) has implemented any risk assessment tool in criminal justice that is based on machine learning.[35] Despite somewhat frequent claims to the contrary in the popular media,[36] the remaining algorithmic tools appear all to be based on standard indices or conventional logistic regression models—not machine-learning algorithms.

For example, one of the more popular non-learning algorithmic tools for bail decisions, the Arnold Foundation's Public Safety Assessment, considers nine factors: the defendant's age, the current violent offense, pending charges at the time of the offense, prior misdemeanor, felony, and violent convictions, prior failure to appear in the past two years and prior to the past two years, and prior sentences to incarceration. It then weighs these factors in varying proportions to determine scores from one to six that predict the defendant's likelihood of failure to appear in court, new criminal activity, and new violent criminal activity, which a court can use in determining whether to grant a defendant pretrial release.[37]

Another non-learning algorithmic tool, known as the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), has been adopted by several state court systems for pretrial decisions. It involves an extensive questionnaire examining issues such as the defendant's prior criminal history, compliance with probation, substance abuse, relationships with others who have been arrested or sent to jail, home and work environment, and personality.[38] The algorithm uses these data points to place the defendant along several "risk scales" purporting to predict the defendant's relative likelihood of pretrial failure (including failure to appear and new felony arrest after pretrial release) and recidivism.[39] Judges deciding whether to approve a defendant for pretrial release or

REVISED: A PORTRAIT OF RIDOC OFFENDERS (Apr. 2011), http://www.doc.ri.gov/administration/planning/docs/LSINewsletterFINAL.pdf.

[35] *See* Richard Berk, *An Impact Assessment of Machine Learning Risk Forecasts on Parole Board Decisions and Recidivism*, 13 J. EXPT. CRIM. 193 (2017). And technically this use in Pennsylvania is by an agency, not a court: the Pennsylvania Board of Probation and Parole. Another state, Maryland, has apparently looked into using machine learning for parole, but does not appear to have implemented it.

[36] *See, e.g.,* Matt O'Brien & Dake Kang, *AI in the Court: When Algorithms Rule on Jail Time*, ASSOCIATED PRESS (Jan. 31, 2018), https://www.apnews.com/ae7b23e20c874800 aa5746b92210 a2dc.

[37] *Risk Factors and Formulas*, PUBLIC SAFETY ASSESSMENT, https://www.psapretrial.org/about/ (last visited Nov. 20, 2019); *see also, e.g.*, N.J. COURTS, PUBLIC SAFETY ASSESSMENT: NEW JERSEY RISK FACTOR DEFINITIONS 1-4 (Dec. 2018), https://njcourts.gov/courts/assets/criminal/psariskfactor.pdf.

[38] *See generally* NORTHPOINTE INC., PRACTITIONER'S GUIDE TO COMPAS CORE (Mar. 19, 2015), http://www.northpointeinc.com/files/technical_documents/Practitioners-Guide-COMPAS-Core-_031915.pdf. While the details of the algorithm are proprietary, investigative journalistic organization ProPublica uncovered the version of the questionnaire used in the Wisconsin state court system. *See Risk Assessment*, https://www.documentcloud.org/documents/2702103-Sample-Risk-Assessment-COMPAS-CORE.html. Other states' courts have adopted COMPAS as well, including Florida, Michigan, New Mexico, and Wyoming. *See Algorithms in the Criminal Justice System*, ELECTRONIC PRIVACY INFO. CTR., https://epic.org/algorithmic-transparency/crim-justice/ (last visited Nov. 20, 2019).

[39] PRACTITIONER'S GUIDE TO COMPAS CORE, *supra* note 38.

analyzing the appropriate sentence to set can then take the values reached by these algorithms into account in their determinations.[40]

A third basic algorithmic tool, LSI-R (Level of Service Inventory-Revised), also aims to predict a defendant's risk of recidivism by weighing a number of factors. These factors include criminal history, educational and employment background, financial, mental, and familial state, substance abuse, and other personal details.[41]

In addition to these three examples, some states have also adopted their own unique risk assessment algorithms.[42] But yet again, simply to be clear, these are not artificial intelligence *per se*: these statistical models develop formulas based off of studying large data sets, and then apply those formulas to the inputs they are given for each defendant, rather than engaging in fully unguided "learning" to figure out what scores to give defendants.

Despite their increasing use by criminal courts, algorithmic risk assessment tools have not avoided scrutiny. Some scholars, lawyers, and concerned citizens challenge the lack of transparency behind some of these algorithms, as some of them are created by private consultants who claim commercial secrecy protection to avoid disclosure.[43] The state of Idaho, in fact, passed a law last year that requires that all pretrial risk assessment tools be transparent, compelling the builders of these tools to make their algorithms' inputs open to public inspection and allow criminal

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[40] *See, e.g.*, Adam Liptak, *Sent to Prison by a Software Program's Secret Algorithms*, N.Y. TIMES (May 1, 2017), https://www.nytimes.com/2017/05/01/us/politics/sent-to-prison-by-a-software-programs-secret-algorithms.html; O'Brien & Kang, *supra* note 36; Ellora Thadaney Israni, *When an Algorithm Helps Send You to Prison*, N.Y. TIMES (Oct. 26, 2017), https://www.nytimes.com/2017/10/26/opinion/algorithm-compas-sentencing-bias.html ("Use of a computerized risk assessment tool somewhere in the criminal justice process is widespread across the United States . . . . States trust that even if they cannot themselves unpack proprietary algorithms, computers will be less biased than even the most well-meaning humans.").

[41] For instance, the Rhode Island Department of Corrections has adopted this test. *See* R.I. DEP'T OF CORRS., *supra* note 34. Courts in other states have also adopted some version of the LSI-R, including California, Colorado, Delaware, Hawaii, Iowa, Oklahoma, and Washington. *See Algorithms in the Criminal Justice System*, *supra* note 38.

[42] *See, e.g.*, BD. OF DIRS. OF THE JUDICIAL CONFERENCE OF IND., *supra* note 34; Susan Turner et al., *Development of the California Static Risk Assessment (CSRA): Recidivism Risk Prediction in the California Department of Corrections and Rehabilitation* 5-6 (U.C. Irvine Ctr. for Evidence-Based Corrections, Working Paper, Sept. 2013), https://ucicorrections.seweb.uci.edu/files/2013/12/Development-of-the-CSRA-Recidivism-Risk-Prediction-in-the-CDCR.pdf (listing factors considered by the California Static Risk Assessment tool); LA. SENTENCING COMM'N, RECOMMENDATIONS OF THE LOUISIANA SENTENCING COMMISSION FOR THE 2010 AND 2011 TERMS 14 (Mar. 1, 2012), http://www.lcle.state.la.us/sentencing_commission/2012_biannual_report_lsc_final.pdf (noting that Louisiana utilizes risk assessment tools for "both inmate management and programming . . . for persons held in state adult correctional facilities and supervision planning . . . for persons under probation or parole supervision provided by the Department"); THE COUNCIL OF STATE GOV'TS JUSTICE CTR., MONTANA COMMISSION ON SENTENCING 41 (Mar. 1-2, 2016), https://csgjusticecenter.org/wp-content/uploads/2016/03/Montana_Commission_on_Sentencing_third_meeting.pdf (noting the use of the Montana Offender Reentry Risk Assessment).

[43] *See, e.g.,* Cade Metz & Adam Satariano, *An Algorithm that Grants Freedom, or Takes it Away*, N.Y. TIMES (Feb 7, 2020), https://www.nytimes.com/2020/02/06/technology/predictive-algorithms-crime.html.

defendants to request access to the calculations and data that determine their risk assessment scores.[44]

Even when the parameters used in the analysis are publicly known, the owners of the risk assessment system will often decline to explain how exactly the factors that go into assessing an individual's likelihood of recidivism or pretrial misbehavior are weighted.[45] As Judge Noel Hillman of the District of New Jersey has put it, "[a] predictive recidivism score may emerge oracle-like from an often-proprietary black box. Many, if not most, defendants . . . will lack the resources, time, and technical knowledge to understand, probe, and challenge" the use of these tools.[46] However, a widely discussed 2016 ProPublica investigation suggested that the COMPAS tool systematically found black defendants to be at a higher risk of recidivism than similarly situated white defendants,[47] raising significant questions about the wisdom of integrating algorithms into judicial decision-making.[48] A recent study from George Mason University, meanwhile, found that the use of an algorithmic risk-assessment tool by Virginia state court judges failed to lower

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[44] IDAHO CODE § 19-1910 (2019).

[45] *See, e.g.*, Noel L. Hillman, *The Use of Artificial Intelligence in Gauging the Risk of Recidivism*, AM. BAR ASS'N (Jan. 1, 2019), https://www.americanbar.org/groups/judicial/publications/judges_journal/2019/winter/the-use-artificial-intelligence-gauging-risk-recidivism/ ("[P]redictive technology becomes another witness against the defendant without a concomitant opportunity to test the data, assumptions, and even prejudices that underlie the conclusion."). Some have raised concerns about the secrecy that the creators of these risk assessment tools maintain over the inner workings of their products:

> No one knows exactly how COMPAS works; its manufacturer refuses to disclose the proprietary algorithm. We only know the final risk assessment score it spits out . . . Something about this story is fundamentally wrong: Why are we allowing a computer program, into which no one in the criminal justice system has any insight, to play a role in sending a man to prison?

Israni, *supra* note 40; *see also* Deirdre K. Mulligan & Kenneth A. Bamberger, *Procurement as Policy: Administrative Process for Machine Learning*, 34 BERKELEY TECH. L.J. 781, 786 (2019) (noting that "government agencies purchasing and using [algorithmic] systems most often have no input into—or even knowledge about—their design or how well that design aligns with public goals and values" and "know nothing about the ways that the system models the phenomena it seeks to predict, the selection and curation of training data, or the use of that data").

[46] Hillman, *supra* note 45; *cf.* Judge Stephanie Domitrovich, *Artificial Intelligence Stepping into Our Courts: Scientific Reliability Gatekeeping of Risk Assessments*, AM. BAR ASS'N (Feb. 3, 2020), https://www.americanbar.org/groups/judicial/publications/judges_journal/2020/winter/artificial-intelligence-stepping-our-courts-scientific-reliability-gatekeeping-risk-assessments/#2 (urging the adoption of best practices to validate risk assessment tools and ensure their reliability).

[47] *See* Julia Angwin et al., *Machine Bias*, PROPUBLICA (May 23, 2016), https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing; *see also* Israni, *supra* note 40; Liptak, *supra* note 40; Ed Yong, *A Popular Algorithm Is No Better at Predicting Crimes Than Random People*, THE ATLANTIC (Jan. 17, 2018), https://www.theatlantic.com/technology/archive/2018/01/equivant-compas-algorithm/550646/.

[48] *See, e.g.*, Cynthia Rudin et al., *The* Age *of Secrecy and Unfairness in Recidivism Prediction* 1 (Duke University, Working Paper, 2019) , https://arxiv.org/pdf/1811.00731.pdf ("[W]e show that COMPAS does not necessarily depend on race, contradicting ProPublica's analysis . . . ."); Anne L. Washington, *How to Argue with an Algorithm: Lessons from the COMPAS-ProPublica Debate* 2-3 (New York University, Working Paper, 2019), https://papers.ssrn.com/sol3/papers.cfm?abstractid=3357874 (providing an alternative framework for evaluating the integrity of predictive algorithms).

incarceration or recidivism rates and that racial disparities in sentencing increased in the courts that most relied on the tool.[49]

To date, the courts have only started to grapple with the legal implications of these algorithmic tools. Most prominently, in *State v. Loomis*, a defendant in Wisconsin state court challenged the state's use of the COMPAS algorithm in sentencing him after he plead guilty.[50] Loomis's COMPAS risk scores indicated that he had a high risk of recidivism; at sentencing, the court relied in part on the fact that he had been "identified, through the COMPAS assessment, as an individual who is at high risk to the community."[51]

In a post-conviction challenge to his sentence, Loomis argued that using the risk assessment violated his due process rights (1) to be sentenced based upon accurate information; (2) to receive an individualized sentence; and (3) to not have gendered assessments be used in sentencing.[52] The trial court denied the motion, holding that it had "used the COMPAS risk assessment to corroborate its findings and that it would have imposed the same sentence regardless of whether it considered the COMPAS risk scores," and the Wisconsin Supreme Court affirmed.[53]

The state Supreme Court rejected Loomis's due process challenges, noting that the variables that the COMPAS algorithms used were publicly available and that the risk assessment's outcome was based fully on either the defendant's answers to the questions or on publicly available information about hist criminal history.[54] As a result, the use of COMPAS complied with due process, since the defendant had the "opportunity to verify that the questions and answers listed on the report were accurate."[55] The court further held that, although the use of risk assessment tools did involve group data, its inclusion among a mix of factors still achieved an individualized sentence for the defendant.[56] Finally, the inclusion of gender in the COMPAS algorithm's analysis did not violate any due process rights absent any proof that the court actually relied on gender as a factor in sentencing, since the algorithm simply accounted for differences in recidivism rates between men and women.[57]

Loomis appealed to the United States Supreme Court.[58] The Court invited the Solicitor General[59] to weigh in, often a sign that the Court recognizes the

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[49] Megan T. Stevenson & Jennifer L. Doleac, *Algorithmic Risk Assessment in the Hands of Humans* 1-6, 36 (Working Paper, 2019), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3489440.
[50] 881 N.W.2d 749 (Wis. 2016).
[51] *Id.* at 755.
[52] *Id.* at 757.
[53] *Id.*
[54] *Id.* at 761.
[55] *Id.*
[56] *Id.* at 764-65. However, this state Supreme Court warned lower courts to be careful given the group-based nature of the COMPAS assessment.
[57] *Id.* at 765-67.
[58] Petition for Writ of Certiorari, Loomis v. Wisconsin, 2017 U.S. LEXIS 4204 (June 26, 2017) (No. 16-6387).
[59] The Solicitor General handles all litigation on behalf of the United States in the U.S. Supreme Court. *See Office of the Solicitor General*, U.S. DEP'T OF JUSTICE, https://www.justice.gov/osg (last visited Nov. 20, 2019).

significant potential value of the case.[60] The Solicitor General's Office argued that the Court should not grant the petition, noting that no division of authority yet existed on the validity of the use of these algorithms and asserting that "[t]he issues that this petition raises . . . would benefit from further percolation. Most of the developments related to the use of actuarial risk assessments at sentencing have emerged within the last several years."[61] Ultimately, the Court declined to take up the case, leaving the issue unresolved.[62]

In another case, *Malenchik v. State*, the defendant pled guilty to a felony and admitted to being a habitual offender.[63] On appeal, the defendant challenged the use of the results of two risk assessment tests (one of which was the LSI-R) in determining his sentence; the tests' results indicated that he was at high risk of recidivism.[64] The Indiana Supreme Court emphasized that the sentence had been based on factors other than the risk assessments, since the trial court had also relied on the defendant's prior criminal history and refusal to accept responsibility for his actions and change his behavior and had not used the algorithm's output as an independent aggravating factor.[65] The court noted that such tools are neither "intended nor recommended to substitute for the judicial function of determining the length of sentence," but are instead "significant sources of valuable information for judicial consideration in deciding whether to suspend all or part of a sentence, how to design a probation program for the offender, whether to assign an offender to alternative treatment facilities or programs, and other such corollary sentencing matters."[66] As a result, the Indiana Supreme Court held that a trial court can properly "supplement and enhance" its evaluation of the evidence before it at sentencing by considering the results of a risk assessment, which can "provide usable information based on extensive penal and sociological research to assist the trial judge in crafting individualized sentencing schemes with a maximum potential for reformation."[67]

Meanwhile, a third case, *State v. Rogers*, involved a claim by a convicted defendant challenging the *lack of* the use of a risk assessment tool in his sentencing. The Supreme Court of Appeals of West Virginia rejected the claim because the

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[60] *See* Loomis v. Wisconsin, 137 S. Ct. 1240 (2017). For discussions of the role of the Solicitor General in influencing the Court's docket and merits decision, see, for example, Ryan C. Black & Ryan J. Owens, *Solicitor General Influence and Agenda Setting on the U.S. Supreme Court*, 64 POL. RES. Q. 765, 766 (2011) ("[W]e find strong support for SG influence. Justices who completely disagree with the SG nevertheless follow her recommendations 35 percent of the time, a number we take to be powerful evidence of influence."); Margaret Meriwether Cordray & Richard Cordray, *The Solicitor General's Changing Role in Supreme Court Litigation*, 51 B.C. L. REV. 1323, 1324 (2010) ("The U.S. Solicitor General, as the U.S. Supreme Court's premier advocate, has long exerted significant influence over both the Court's case selection decisions and its substantive decisions on the merits.").

[61] Brief for the United States as Amicus Curiae at 21-22, Loomis v. Wisconsin, 2017 U.S. LEXIS 4204 (June 26, 2017) (No. 16-6387).

[62] *See Loomis*, 2017 U.S. LEXIS 4204, at *1.

[63] 928 N.E.2d 564, 566 (Ind. 2010).

[64] *Id.* at 566-67.

[65] *Id.* at 568.

[66] *Id.* at 573.

[67] *Id.* at 573-75.

defendant failed to enter a proper objection at the time of initial sentencing. But Justice Loughry, in a separate concurring opinion, argued that a risk assessment algorithm is "merely a tool that may be used by [trial court] judges during sentencing," a process over which judges have broad discretion and that courts are under no obligation to use it.[68]

Finally, in a few criminal appeals, defendants have questioned whether prosecutors must disclose the results of algorithmic facial recognition or risk assessment tools to defense counsel as part of their duty to turn over exculpatory evidence under *Brady v. Maryland*.[69] The courts that have handled these cases have avoided delving into issues concerning the algorithmic nature of any of the particular tools used in those cases, since they concluded either that the tools were not actually used in prosecuting the defendant or that the failure to disclose their use did not prejudice the defendant.[70]

Although it is still early in the judiciary's assessment of legal issues surrounding courts' use of algorithmic tools, it seems noteworthy that, in all the cases decided to date that have actually wrestled with these issues, courts appear to have taken pains to emphasize that such tools only serve as one of multiple factors that a human judge takes into account in reaching a decision. Perhaps this suggests that, as long as humans remain in the loop, whether with standard algorithmic tools or even with machine-learning algorithms, courts' reliance on algorithms will continue to win approval.[71]

C. *Online Dispute Resolution*

Online Dispute Resolution (ODR) has arisen in recent years as a tool for resolving disagreements among parties using technology, growing in part out of prior developments in the field of Alternative Dispute Resolution (ADR). ADR is a term that refers to a range of methods such as mediation and arbitration that aim to settle disputes without the use of litigation and the court system.[72] ODR mechanisms first mimicked ADR approaches to conflict resolution before evolving

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[68] No. 14-0373, 2015 WL 869323, at *2 (W. Va. Jan. 9, 2015); *id.* at *4–5 (Loughry, J., concurring).
[69] For a discussion of these appeals, see AI NOW INST., LITIGATING ALGORITHMS 2019 REPORT 30 (2019), https://ainowinstitute.org/litigatingalgorithms-2019-us.pdf. The Supreme Court's decision in *Brady v. Maryland* can be found at 373 U.S. 83 (1963).
[70] AI NOW INST., *supra* note 69; *see also* Lynch v. State, 260 So. 3d 1166, 1169-70 (Fla. Dist. Ct. App. 2018), *review denied*, 2019 WL 3249799 (Fla. July 19, 2019).
[71] *See, e.g.*, *Malenchik*, 928 N.E.2d at 568 ("[T]he trial court's sentencing decision was clearly based on factors apart from the defendant's LSI-R and SASSI results. . . . The trial judge did not rely on either the LSI-R or SASSI as an independent aggravating factor in deciding to impose more than the advisory sentence."). *See generally* Melissa Hamilton, *Risk-Needs Assessment: Constitutional and Ethical Challenges*, AM. CRIM. L. REV. 231 (2015); Roger K. Warren, *Evidence-Based Sentencing: The Application of Principles of Evidence-Based Practice to State Sentencing Practice and Policy*, 43 U.S.F. L. REV. 585 (2009).
[72] *See* ETHAN KATSH & ORNA RABINOVICH-EINY, DIGITAL JUSTICE 33-34 (2017); *Online Dispute Resolution Moves From E-Commerce to the Courts*, PEW CHARITABLE TRS. (June 4, 2019), https://www.pewtrusts.org/en/research-and-analysis/articles/2019/06/04/online-dispute-resolution-moves-from-e-commerce-to-the-courts [hereinafter *Online Dispute Resolution I*]; *Alternative Dispute Resolution*, LEGAL INFO. INST., https://www.law.cornell.edu/wex/alternative_dispute_resolution (last updated June 8, 2017).

into their current forms, which harness the advantages of technology to aid their mission.[73]

The initial growth of ODR has been largely driven by the private sector.[74] Most notably, eBay and PayPal have developed ODR systems to handle the millions of disputes that regularly arise on their platforms from and among users.[75] Realizing that they could not afford to hire enough human mediators to resolve all of these disputes or arrange for parties to videoconference with each other, these companies leveraged the extensive amounts of data they had collected on consumer behavior and usage.[76] Their ODR systems aim to prevent or amicably resolve as many disputes as possible and to decide the remainder quickly. To do so, they generally first diagnose the problem, working directly with the complainant; they then move to direct negotiations (aided by technology) and ultimately allow the company to decide the case if the parties are not able to amicably resolve matters on their own.[77] As the success of these systems inspired other firms to develop similar and increasingly sophisticated programs, algorithms have become a more prominent dispute resolution solution, allowing companies to automate away many (if not all) of the steps of decision-making process.[78] For example, Amazon has developed algorithms that can resolve a consumer complaint about a defective product without requiring any human intervention.[79]

Some courts have also begun experimenting with ODR as a mechanism to attempt to resolve lawsuits without requiring the use of judicial decision-making. Although much of the innovation in this area has occurred in other parts of the world, dozens of state and local courts in the United States, including in Michigan, Ohio, California, and Utah, have adopted some form of "court ODR" in cases involving small claim civil matters, traffic violations, outstanding warrant cases, and low-conflict family court cases.[80] What counts as an ODR system can vary from a simple website that facilitates entering pleas for traffic tickets online to an online portal for engaging in asynchronous negotiations. These are not mandatory systems in any jurisdiction of which we are aware, but instead they are offered as an option to avoid appearing in court. In jurisdictions with these systems, parties

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[73] *See* KATSH & RABINOVICH-EINY, *supra* note 72*; Online Dispute Resolution I*, *supra* note 72.

[74] *See Online Dispute Resolution I*, *supra* note 72.

[75] *See* BARTON & BIBAS, *supra* note 21, at 111 (2017); KATSH & RABINOVICH-EINY, *supra* note 72, at 34-35.

[76] BARTON & BIBAS, *supra* note 21, at 111; KATSH & RABINOVICH-EINY, *supra* note 72, at 34-35.

[77] COLIN RULE & AMY J. SCHMITZ, THE NEW HANDSHAKE: ONLINE DISPUTE RESOLUTION AND THE FUTURE OF CONSUMER PROTECTION 37 (2017) ("Each stage acted like a filter, with the objective being to minimize the flow of cases that made it to the end."); *see also* BARTON & BIBAS, *supra* note 21, at 111-115; KATSH & RABINOVICH-EINY, *supra* note 72, at 34-36. We note that Colin Rule helpfully describes the stages of an ODR process using the "DNMEA" mnemonic: Diagnosis, Negotiation, Mediation, Evaluation, and Appeal.

[78] KATSH & RABINOVICH-EINY, *supra* note 72, at 46-48.

[79] *Id.* at 48.

[80] KATSH & RABINOVICH-EINY, *supra* note 72, at 161-62; *Online Dispute Resolution Offers a New Way to Access Local Courts*, PEW CHARITABLE TRUSTS (Jan. 4, 2019), https://www.pewtrusts.org/en/research-and-analysis/fact-sheets/2019/01/online-dispute-resolution-offers-a-new-way-to-access-local-courts [hereinafter *Online Dispute Resolution II*].

are notified of the ODR option via mailings or websites.[81] Parties can access the ODR system at any time, and with the more interactive systems they can communicate and negotiate with each other, obtain legal information and suggested resolutions from the system, and easily manage electronic documents—all without having to see the inside of a courtroom.[82] These systems can usually reach resolution in a dispute faster and at lower cost to the parties and are far more accessible than traditional court-centered adjudication.[83]

ODR provides an emerging avenue for litigants and courts to engage in dispute resolution outside of the presence of a courtroom and absent a human judge. Court ODR systems, as well as the private-sector iterations that inspired them, have increasingly adopted automated processes and rely on algorithmic tools to aid in reaching what some observers characterize as fair and low-cost solutions to the parties' disputes.[84] As some researchers have already begun to note, court systems could take these algorithms to the next "level" of autonomy by integrating artificial intelligence into ODR processes, allowing for increasingly automated forms of decision-making.[85]

II. ARTIFICIAL INTELLIGENCE IN THE ADMINISTRATIVE STATE

Government agencies have long pursued the use of information technology to support vital services and programs. Even outside of the military, intelligence-gathering, and space exploration contexts, computers have been used for decades by government agencies to support administration and data management for tasks including tax collection and the operation of large national benefits programs such as Social Security and Medicare.[86] The technologies used by government have tended to lag behind those deployed in the private sector. Federal and state agencies relied on mainframe computers, for example, long after the personal computer revolution hit the private sector in the 1980s, and they continue to remain behind the innovation curve to this day.[87] Many government computer systems have grown

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[81] KATSH & RABINOVICH-EINY, *supra* note 72, at 161-62; *Online Dispute Resolution II*, *supra* note 80.

[82] *Online Dispute Resolution II*, *supra* note 80.

[83] *Online Dispute Resolution I*, *supra* note 72.

[84] KATSH & RABINOVICH-EINY, *supra* note 72, at 163 ("The use of ODR in courts is also introducing algorithms into the judicial decision-making process."); Loïc E. Coutelier, *The New Frontier of Online Dispute Resolution: Online Divorce Mediation*, AM. BAR ASS'N (Apr. 1, 2016), https://www.americanbar.org/groups/young_lawyers/publications/tyl/topics/dispute-resolution/new-frontier-online-dispute-resolution-online-divorce-mediation/ (discussing a form of ODR used in divorce mediation that relies on "an innovative algorithm that uses game theory negotiation to maximize the return for divorcing couples who are dividing assets").

[85] *See generally* Arno R. Lodder & John Zeleznikow, *Artificial Intelligence and Online Dispute Resolution*, *in* ONLINE DISPUTE RESOLUTION: THEORY AND PRACTICE 73-94 (Mohamed S. Abdel Wahab et al. eds., 2012).

[86] Harold C. Relyea & Henry B. Hogue, *A Brief History of the Emergence of Digital Government in the United States*, *in* DIGITAL GOVERNMENT 16 (Alexei Pavlichev & G. David Garson eds., 2004).

[87] Jack Moore, *The Crisis in Federal IT that's Scarier than Y2K Ever Was*, NEXTGOV (Nov. 20, 2015), http://www.nextgov.com/cio-briefing/2015/11/crisis-federal-it-rivals-y2k/123908/; Tod Newcombe, *The Complicated History of Government Technology*, GOVERNING (Oct. 2, 2017), https://www.govtech.com/computing/The-Complicated-History-of-Government-Technology.html.

quite antiquated. As of 2016, auditors could report that three-quarters of annual federal spending on computer technology in the United States is devoted to "legacy systems" which "are becoming increasingly obsolete" due to "outdated software languages and hardware parts that are unsupported."[88]

Still, the internet revolution in the 1990s did prompt state and federal government agencies to begin to digitize many of their services and make greater use of the worldwide web. Initially, of course, the movement was slow. According to one survey, by the year 2000, states had websites containing an average each of only about four automated or online governmental services.[89] The most popular such digitized service at that time: applying for a state government job (which was available in 32 states).[90] The second most popular was electronic filing of income taxes (24 states) and the third most popular was the online renewal of drivers licenses (17 states).[91] Today, all states have these basic services digitized—and many more services as well.

The federal government adopted the E-Government Act of 2002 "to develop and promote electronic Government services and processes" and "[t]o promote use of the Internet and other information technologies to provide increased opportunities for citizen participation in Government."[92] That law established a federal Office of Electronic Government, imposed a duty on all federal agencies to make vast quantities of government information available online, and generally to accept online submissions of public comments on proposed regulations.[93] The federal government has since created portals such as *Regulations.gov* and *Data.gov* to make available online massive amounts of information previously housed in paper records or internal government computers.[94]

Today, the United States is regarded as among the nations that has made the most advanced progress in implementing practices of e-government. According to the latest e-government ranking by the United Nations, the United States places second among all countries for "online service delivery" (tying with Singapore, and just behind Denmark). [95] It also ranks among the top nations for "e-participation."[96]

These rankings suggest that, even if administrative agencies in the United States may have been slower out of the starting gate than the private sector in their use of information technology, they appear ahead of many counterpart governments elsewhere in the world. They have also moved much earlier to digitize their

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[88] U.S. GOV'T ACCOUNTABILITY OFFICE, GAO-16-696T, INFORMATION TECHNOLOGY: FEDERAL AGENCIES NEED TO ADDRESS AGING LEGACY SYSTEMS (2016), https://www.gao.gov/assets/680/677454.pdf (testimony of David A. Powner, Director, Information Technology Management Issues).
[89] Jane E. Fountain, *The Virtual State: Transforming American Government?*, 90 NAT'L CIV. REV. 241, 242 (2001).
[90] *Id*.
[91] *Id*.
[92] E-Government Act of 2002, 107 Pub. L. No. 347, § 2, 116 Stat. 2899, 2900-01.
[93] *Id.* § 3602.
[94] For discussion of these and related efforts, see WHITE HOUSE ARCHIVES, THE OBAMA ADMINISTRATION'S COMMITMENT TO OPEN GOVERNMENT: A STATUS REPORT (2011), https://obamawhitehouse.archives.gov/sites/default/files/opengov_report.pdf.
[95] UNITED NATIONS, UNITED NATIONS E-GOVERNMENT SURVEY 2018, at 89, 91, 114 (2018).
[96] *Id*.

operations and services than has the U.S. court system. In this respect, administrative agencies are well along a path that will support greater use of machine learning.

Some agencies have undertaken focused efforts to make data more easily accessible for use in machine-learning applications. For example, officials at the Federal Deposit Insurance Corporation have expressly focused on developing "the back-end disciplines of in-memory analytics, big data, and data quality."[97] Staff at the Federal Communications Commission (FCC) established a Data Innovation Initiative with similar goals.[98] Financial regulators have worked to create a dedicated "legal entity identifier" to be able to link disparate transactional and other data to the corresponding business entities.[99] The Environmental Protection Agency has built databases that can be used to train algorithms,[100] while the Food and Drug Administration has tapped into cloud storage capacity to give the agency the ability to analyze Big Data.[101]

Beyond these data-centered building blocks to artificial intelligence, U.S. administrative agencies are generally light years ahead of the U.S. judicial system in terms of employing algorithmic tools. After all, algorithmic tools of the statistical kind have long been a staple of administrative decision-making, especially when these agencies set policies and regulations.[102] Some government agencies, such as the U.S. Department of Commerce, even have data collection and analysis as among their principal responsibilities.[103] As a result, it is also not surprising that administrative agencies are ahead of the courts in terms of their use of full-fledged machine-learning tools, something that the courts have yet to deploy. Admittedly, the use of machine learning within administrative agencies is not yet as extensive as it is in the private sector, but artificial intelligence is beginning to emerge to assist with important administrative functions—even though, again, we know of no example where artificial intelligence has fully replaced human decision-making.

We also know of no comprehensive survey of all uses of machine learning by administrative agencies at the state and federal levels. A team of researchers from Stanford University and New York University (NYU), however, is currently

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[97] U.S. FED. DEPOSIT INS. CORP., BUSINESS TECHNOLOGY STRATEGIC PLAN 2013–2017 (2013), https://www.fdic.gov/about/strategic/it_plan/BusinessTechnology StrategicPlan2013-2017.pdf.
[98] *See* Michael Byrne, *Big Data*, FCC BLOG (Oct. 28, 2010, 1:06 PM), https://www.fcc.gov/news-events/blog/2010/10/28/big-data.
[99] *See* Matthew Reed, *Legal Entity Identifier System Turns a Corner*, FINRESEARCH.GOV: FROM THE MANAGEMENT TEAM (July 3, 2014), https://financialresearch.gov/from-the-management-team/2014/07/03/legal-entity-identifier-system-turns-a-corner/.
[100] *See EPA's Cross-Agency Data Analytics and Visualization Program*, EPA, https://web.archive.org/web/20160414154548/https://www.epa.gov/toxics-release-inventory-tri-program/epas-cross-agency-data-analytics-and-visualization-program (last updated Dec. 29, 2015).
[101] *See* Taha Kass-Hout, *FDA Leverages Big Data via Cloud Computing*, FDA VOICE (June 19, 2014), http://blogs.fda.gov/fdavoice/index.php/2014/06/fda-leverages-big-data-via-cloud-computing.
[102] For more recent discussions of the use of algorithmic analysis in public administration, see generally, for example, ROBERT D. BEHN, THE PERFORMANCESTAT POTENTIAL: A LEADERSHIP STRATEGY FOR PRODUCING RESULTS (2014); DONALD F. KETTL, LITTLE BITES OF BIG DATA FOR PUBLIC POLICY (2018);MONEYBALL FOR GOVERNMENT (Jim Nussle & Peter Orszag eds., 2014).
[103] *See generally* MICHAEL LEWIS, THE FIFTH RISK (2018).

engaged in a multi-year effort, involving more than two dozen researchers with backgrounds in law and computer science, to survey the use of machine learning by the federal government and develop a series of case studies.[104] Although this team has yet to issue a written report, its leaders did share some initial findings both via email correspondence and orally at a public meeting of the Administrative Conference of the United States in June 2019. The research team has looked carefully through a broad range of public sources to find references to possible machine-learning uses at about 140 federal agencies, yielding a total of 175 "use cases" involving the reliance on algorithms[105]—the "bulk" of which appear to have been "true AI in the modern learning sense as opposed to processed automation and conventional statistics."[106] However, these examples were not distributed evenly across agencies: the Securities and Exchange Commission, for example, had eleven distinct use cases, while about half of the agencies in the study had none.[107] Furthermore, when team members with computer science backgrounds looked closely at each use, they could find only about 17 percent that could be ranked as having a higher level of sophistication,[108] suggesting that there remains "still a fair bit of work to be done to close the private/public sector technology gap."[109] Finally, the researchers appear not entirely confident that all of their use case actually entailed full machine learning systems, as they reported "some degree of puffery amongst agencies when they describe the adoption of machine learning and AI tools."[110]

It is also not entirely clear, based on what the Stanford-NYU team has reported to date, the precise stage of implementation at which all of the use cases find themselves. Some of these efforts appear to be prototypes, pilots, or even research studies. Still, the Stanford-NYU team's finding of 175 use cases across the federal government at least suggests a plausible upper bound of the current extent of uses of machine learning at the federal level. Obviously, still more uses exist at

[104] David Engstrom, Remarks at the 71st Plenary Session of the Administrative Conference of the United States (June 13, 2019) (transcript on file with authors). In the early part of this century, the federal General Accountability Office (GAO) conducted a survey of more than 125 federal agencies and reported that 52 relied on some form of "data mining," which the GAO defined broadly "as the application of database technology and techniques—such as statistical analysis and modeling—to uncover hidden patterns and subtle relationships in data and to infer rules that allow for the prediction of future results." U.S. GEN ACCOUNTABILITY OFFICE, GAO-04-548, DATA MINING: FEDERAL EFFORTS COVER A WIDE RANGE OF USES 4 (2004). The GAO did not report whether any of these applications relied on machine learning rather than traditional analytic tools.

[105] The researchers' search turned up the use of algorithms at 142 federal agencies with 400 FTEs or more. E-mail from David Engstrom, Professor of Law & Assoc. Dean, Stanford Law Sch. to Cary Coglianese, Professor of Law, U. of Pa. Law Sch. (Dec. 12, 2019) (on file with authors).

[106] Dan Ho, Remarks at the 71st Plenary Session of the Administrative Conference of the United States (June 13, 2019) (transcript on file with authors). Of the 110 use cases where the researchers were able to assess algorithmic sophistication, they coded about 30 of these as falling in the "higher" range of sophistication, slightly less than 50 in the "medium" range, and a bit less than 30 in the "lower" range. E-mail from David Engstrom to Cary Coglianese, *supra* note 105.

[107] E-mail from David Engstrom to Cary Coglianese, *supra* note 105. The researchers found that only 69 of the 142 agencies (49%) had even a single use of an algorithmic tool. *Id.*

[108] *See supra* notes 104–105.

[109] Dan Ho, Remarks, *supra* note 106.

[110] *Id*.

the state and local government level. We cannot purport to chronicle all instances of administrative machine learning in this Article, but instead we provide a range of examples to convey the variety of uses to which machine learning is being put by various agencies throughout the United States.

It is revealing that, among the use cases the Stanford-NYU team identified, the largest proportion (36%) were devoted to enforcement targeting—that is, helping identify cases of possible fraud or regulatory violations have human auditors or inspectors follow up to investigate.[111] We thus first proceed in the next section to provide illustrative instances of machine learning used in the context of enforcement. We then proceed with examples in government services and program administration. Finally, we turn to a discussion of some of the merits, controversies, and legal issues surrounding the use of artificial intelligence in the administrative setting. Our discussion throughout both sections includes examples of machine learning at the federal, state, and local levels of government.

A. *Enforcement*

It is a common refrain that administrative agencies have more problems to deal with than they have resources to devote to solving them. Perhaps nowhere could this be more accurate than in the context of administrative enforcement. Agencies have limited number of auditors, inspectors, and other enforcement personnel who must oversee a vast number of individuals and businesses to ensure their compliance with myriad pages of laws and regulations. The federal Occupational Safety and Health Administration, for instance, has no more than about 2,000 inspectors who oversee more than eight million workplaces employing about 130 million workers.[112] To deploy these limited oversight resources smartly, agencies need to know which businesses or individuals are most likely to require oversight. Machine-learning algorithms can provide forecasts of the likelihood of violations, thus helping agencies allocate resources and decide which regulated entities to target.

The U.S. Internal Revenue Service (IRS), for example, began developing in 2001 machine learning risk tools to integrate data from prior tax records, as well as data from other government agencies, to help it predict cases of possible tax fraud and prioritize which taxpayers to target for auditing.[113] More recently, the IRS developed a machine-learning program that uses credit card information and other third-party data to forecast the probability of underreporting by businesses.[114] The

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[111] *Id.*

[112] *Commonly Used Statistics*, OCCUPATIONAL SAFETY & HEALTH ADMIN., https://www.osha.gov/oshstats/commonstats.html (last visited Nov. 20, 2019).

[113] Jane Martin & Rick Stephenson, Risk-Based Collection Model Development and Testing (June 7, 2005), http://www.irs.gov/pub/irs-soi/05stephenson.pdf; David DeBarr & Maury Harwood, Relational Mining for Compliance Risk (June 2, 2004), http://www.irs.gov/pub/irs-soi/04debarr.pdf.

[114] *See* Chris Wagner et al., *IRS Policy Implementation Through Systems Programming Lacks Transparency and Precludes Adequate Review*, *in* 2010 ANNUAL REPORT TO CONGRESS 71, 76 (2010), http://www.irs.gov/pub/irs-utl/2010arcmsp5_policythruprogramming.pdf; U.S. TREASURY INSPECTOR GEN. FOR TAX ADMIN., 2014-20-088, THE INFORMATION REPORTING AND DOCUMENT

Securities and Exchange Commission similarly uses machine learning and natural language processing to identify potential instances of insider trading or "bad apple" investment advisers or brokers.[115] Meanwhile, the federal agency that oversees Medicare relies in part on machine-learning algorithms to help it identify possible leads for its fraud investigators to pursue.[116] Federal immigration agencies have also increasingly relied on automated processes to help in identifying, monitoring, and apprehending immigrants who are unlawfully in the United States.[117]

A number of state and local law enforcement authorities use algorithmic tools—some of which appear to be based on machine learning—in deciding where to send police patrols. Starting with a widely discussed CompStat initiative in New York City in the 1990s (which was not machine-learning based), many police departments across the United States have taken a more systematic approach to allocating law enforcement resources by using performance metrics and data analysis.[118] Today, this "moneyballing" effort includes both "place-based" and "person-based" predictive policing tools.[119] Place-based tools help police identify areas of a city that have a greater propensity for crime and may merit greater police patrols. For example, at least a dozen or more cities using a vendor-developed software called PredPol, which uses a proprietary algorithm to identify areas of a city which are more likely to be prone to criminal activity so that additional police resources can be allocated to those areas.[120] By contrast, the City of Los Angeles Police Department uses a Real-Time Analysis Critical Response (RACR)

MATCHING CASE MANAGEMENT SYSTEM COULD NOT BE DEPLOYED (2014), https://www.treasury.gov/tigta/auditreports/2014reports/201420088fr.pdf; *cf.* Lynnley Browning, *Computer Scientists Wield Artificial Intelligence to Battle Tax Evasion*, N.Y. TIMES (Oct. 9, 2015), https://www.nytimes.com/2015/10/10/business/computer-scientists-wield-artificial-intelligence-to-battle-tax-evasion.html (discussing a study that developed an artificial intelligence tool that the IRS could use to detect certain tax shelters used by corporate entities).

[115] Pam Karlan & Joe Bankman, *Artificial Intelligence and the Administrative State with Guests David Engstrom and Cristina Ceballos*, STANFORD LEGAL (2019), https://law.stanford.edu/stanford-legal-on-siriusxm/artificial-intelligence-and-the-administrative-state-with-guests-david-engstrom-and-cristina-ceballos/; David Freeman Engstrom & Daniel E. Ho, *Algorithmic Accountability in the Administrative State* 14-18 (Ctr. for the Study of the Admin. State, Working Paper No. 19-34, 2019), https://administrativestate.gmu.edu/wp-content/uploads/sites/29/2019/11/Engstrom-Ho-Algorithmic-Accountability-in-the-Administrative-State.pdf.

[116] Transcription, *supra* note 104 (statement of David Engstrom).

[117] Anil Kalhan, *Immigration Policing and Federalism Through the Lens of Technology, Surveillance, and Privacy*, 74 OHIO ST. L. REV. 1105, 1122-34 (2013).

[118] By the end of the 1990s, a third of the largest police departments in the United States reported using a program like Compstat. DAVID WEISBURD ET AL., POLICE FOUNDATION REPORT: THE GROWTH OF COMPSTAT IN AMERICAN POLICING(April 2004), http://glenn.osu.edu/faculty/glenn-faculty/worley/June%2027%20-%20Reading%201%20-%20The%20Growth%20of%20Compstat%20in%20American%20Policing.pdf.

[119] For the distinction between place-based and person-based prediction, see Ángel Díaz, *New York City Police Department Surveillance Technology*, BRENNAN CTR. FOR JUSTICE (Oct. 7, 2019), https://www.brennancenter.org/sites/default/files/2019-10/2019_NewYorkPolicyTechnology.pdf.

[120] Randy Rieland, *Artificial Intelligence is Now Used to Predict Crime. But is it Biased?,* SMITHSONIAN (Mar. 5, 2018), https://www.smithsonianmag.com/innovation/artificial-intelligence-is-now-used-predict-crime-is-it-biased-180968337/; *see also* ANDREW GUTHRIE, THE RISE OF BIG DATA POLICING SURVEILLANCE, RACE, AND THE FUTURE OF LAW ENFORCEMENT (2017); Erica Goode, *Sending the Police Before There's a Crime*, N.Y. TIMES (Aug. 15, 2011), https://www.nytimes.com/2011/08/16/us/16police.html.

system and the New York City Police Department uses a machine learning tool called Patternizr; these tools are person-based: that is, they integrate information, detect patterns in crime incidents, and find linkages between incidents in an effort to identify alleged perpetrators.[121] Meanwhile, dozens of cities, including New York and Milwaukee, are using a tool called ShotSpotter that alerts police to the locations of shootings based on the sound of gunfire.[122] Recent reports indicate that the Federal Bureau of Investigation and a number of state and local law enforcement agencies are using facial recognition tools marketed by private-sector firms such as Amazon in an effort to identify criminal suspects.[123] In May 2019, the city of San Francisco became the first major U.S. city to place restrictions on law enforcement's use of facial recognition and other surveillance tools.[124] Other cities are considering similar restrictions.

B. *Services and Program Administration*

Just as police departments in major U.S. cities have deployed machine-learning tools to assist with law enforcement efforts, cities are also using machine learning to support other key government functions.[125] The New York City Fire Department, for example, follows its police counterparts in using machine-learning algorithms to allocate and target its limited number of building inspectors that check for compliance with fire-related ordinances.[126] In fact, New York City has established a central Office of Data Analytics, which works to integrate data from across the city and develop "analytics tools to prioritize risk more strategically, deliver services more efficiently, enforce laws more effectively and increase transparency."[127] Other cities have similarly created special offices or teams

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[121] Phil Goldstein, *How Pattern Recognition and Machine Learning Helps Public Safety Departments*, STATETECH (May 3, 2019), https://statetechmagazine.com/article/2019/05/how-pattern-recognition-and-machine-learning-helps-public-safety-departments-perfcon; Caroline Haskins, *Dozens of Cities Have Secretly Experimented with Predictive Policing Software*, VICE (Feb. 6, 2019), https://www.vice.com/en_us/article/d3m7jq/dozens-of-cities-have-secretly-experimented-with-predictive-policing-software.

[122] Chris Weller, *There's a Secret Technology in 90 US Cities That Listens for Gunfire 24/7*, BUS. INSIDER (June 27, 2017), https://www.businessinsider.com/how-shotspotter-works-microphones-detecting-gunshots-2017-6.

[123] *See, e.g.,* Jon Schuppe, *Facial Recognition Gives Police a Powerful New Tracking Tool. It's Also Raising Alarms*, NBC NEWS (July 30, 2018), https://www.nbcnews.com/news/us-news/facial-recognition-gives-police-powerful-new-tracking-tool-it-s-n894936; Jon Schuppe, *How Facial Recognition Became a Routine Policing Tool in America*, NBC NEWS (May 11, 2019), https://www.nbcnews.com/news/us-news/how-facial-recognition-became-routine-policing-tool-america-n1004251.

[124] San Francisco Ordinance on Acquisition of Surveillance Technology, No. 190110 (May 6, 2019), https://sfgov.legistar.com/View.ashx?M=F&ID=7206781&GUID=38D37061-4D87-4A94-9AB3-CB113656159A

[125] *See, e.g.*, Hannah Bloch-Wehba, *Access to Algorithms*, 88 FORDHAM L. REV. (forthcoming 2020) (manuscript at 15-16), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3355776.

[126] Brian Heaton, *New York City Fights Fire with Data*, GOV'T TECH. (May 15, 2015), http://www.govtech.com/public-safety/New-York-City-Fights-Fire-with-Data.html.

[127] *About the Office of Data Analytics*, NYC ANALYTICS, https://www1.nyc.gov/site/analytics/about/about-office-data-analytics.page (last visited Nov. 20, 2019).

devoted to data analysis and prediction.[128] Los Angeles has established a formal partnership, the Data Science Federation, with local colleges and universities to promote "predictive . . . analysis that will help drive data driven decision making within the city."[129] The City of Chicago worked with a consortium of university partners to create a SmartData Platform which helps facilitate the use of machine learning in support of city services.[130]

Cities have employed these tools for a variety of purposes. In Chicago, some of these services supported by machine-learning tools include health inspections of restaurants, with inspectors assigned based on the algorithmic forecasts of the establishments posing the greatest risks.[131] Both Chicago and Washington, D.C., are using machine learning to optimize rodent bait placement throughout their cities.[132] In Flint, Michigan, following a major fiasco in the management of the city's water supply, officials have benefited from machine-learning predictions to identify priorities for replacing pipes contributing to lead contamination.[133] In Los Angeles, traffic lights operate automatically based on a machine-learning system that optimizes for congestion avoidance using data fed by a network of sensors in the city's streets.[134] Johnson County in Kansas has used algorithmic determinations of risk to determine how to allocate its social service counselors and mental health professionals.[135] Allegheny County in Pennsylvania has relied on machine learning in developing a predictive tool to help screen the many phone referrals made to the county's child protective services hotline for risk of future abuse or neglect and help inform decisions about which complaints merit further intervention.[136]

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[128] *See, e.g., Analytics Team*, CITY OF BOSTON, https://www.boston.gov/departments/analytics-team (last visited Nov. 20, 2019); *Data Science*, CITY OF CHICAGO, https://www.chicago.gov/city/en/depts/doit/provdrs/data_sciences.html (last visited Nov. 20, 2019).

[129] *About Us*, DATA SCIENCE, https://datasciencefederation.lacity.org/about-us (last visited Nov. 20, 2019).

[130] Ash Center Mayor's Challenge Research Team, *Chicago's SmartData Platform: Pioneering Open Source Municipal Analytics*, DATA-SMART CITY SOLUTIONS (Jan. 8, 2014), http://datasmart.ash.harvard.edu/news/article/chicago-mayors-challenge-367.

[131] Stephen Goldsmith, *Chicago's Data-Powered Recipe for Food Safety*, DATA-SMART CITY SOLUTIONS (May 21, 2015), https://datasmart.ash.harvard.edu/news/article/chicagos-data-powered-recipe-for-food-safety-688. Boston developed similar restaurant-inspection algorithms through a crowdsourcing project. *See* Edward Glaeser et al., *Crowdsourcing City Government: Using Tournaments to Improve Inspection Accuracy*, 106 AM. ECON. REV. 114 (2016).

[132] Linda Poon, *Will Cities Ever Outsmart Rats?*, CITYLAB (Aug. 9, 2017), https://www.citylab.com/solutions/2017/08/smart-cities-fight-rat-infestations-big-data/535407/.

[133] Gabe Cherry, *Google, U-M to Build Digital Tools for Flint Water Crisis*, UNIV. OF MICH. NEWS (May 3, 2016), http://ns.umich.edu/new/multimedia/videos/23780-google-u-m-to-build-digital-tools-for-flint-water-crisis.

[134] Ian Lovett, *To Fight Gridlock, Los Angeles Synchronizes Every Red Light*, N.Y. TIMES (Apr. 1, 2013), http://www.nytimes.com/2013/04/02/us/to-fight-gridlock-los-angeles-synchronizes-every-red-light.html; David Z. Morris, *How Swarming Traffic Lights Could Save Drivers Billions of Dollars*, FORTUNE (July 13, 2015, 4:47 PM), http://fortune.com/2015/07/13/swarming-traffic-lights.

[135] Robert Sullivan, *Innovations in Identifying People Who Frequently Use Criminal Justice and Healthcare Systems*, POLICY RES. ASSOCIATES (May 16, 2018), https://www.prainc.com/innovations-identification-cj-healthcare/.

[136] RHEMA VAITHIANATHAN ET AL., DEVELOPING PREDICTIVE RISK MODELS TO SUPPORT CHILD MALTREATMENT HOTLINE SCREENING DECISIONS (2019), https://www.alleghenycountyanalytics.

The Data-Smart City Solutions initiative at Harvard University's John F. Kennedy School of Government has cataloged sixty-four uses of data analytics by local governments, some but not all involving machine learning.[137] Its list includes tasks as varied as identifying children who could benefit from mentoring programs, prioritizing trees for trimming, and identifying businesses that might be underpaying taxes.[138] Meanwhile, the Penn Program on Regulation's Optimizing Government project has chronicled other local government efforts either to adopt or study the possibility of using machine learning or other predictive analytics tools to aid with a wide range of purposes, including the following: early intervention academic support for public school students; detection of problems with water infrastructure, waste, and pollution; economic blight prevention; crime forecasting by police departments and detection of risks to police officers from interactions with members of the public; and improvement of city services, public transportation, and public health.[139]

At the federal level, too, predictive analytic tools including machine learning have been put to varied uses. One of the earliest uses of machine learning by the federal government actually helped spur innovations in the technique: the U.S. Postal Service's use of artificial intelligence to support automatic handwriting detection and mail sorting.[140] In addition, scientists at the National Oceanic and Atmospheric Administration have relied on machine learning for weather forecasting.[141] Risk analysts at the Environmental Protection Agency have used machine learning to forecast the likelihood that certain chemicals are toxic and need further study and management.[142] The Food and Drug Administration has employed machine learning to extract information from adverse event reports about

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us/wp-content/uploads/2019/05/16-ACDHS-26_PredictiveRisk_Package_050119_FINAL-2.pdf; *see also* Dan Hurley, *Can an Algorithm Tell When Kids Are in Danger?*, N.Y. TIMES (Jan. 2, 2018), https://www.nytimes.com/2018/01/02/magazine/can-an-algorithm-tell-when-kids-are-in-danger.html.

[137] *A Catalog of Civic Data Use Cases*, HARVARD KENNEDY SCHOOL: DATA-SMART CITY SOLUTIONS (Oct. 9, 2019), https://datasmart.ash.harvard.edu/news/article/how-can-data-and-analytics-be-used-to-enhance-city-operations-723.

[138] *Id.*

[139] *Uses in Government*, *supra* note 6. We acknowledge, however, that descriptive materials available on these various uses do not always make it entirely clear which of these efforts involved actual machine learning versus other kinds of predictive analytic techniques.

[140] One of the first automatic techniques for detecting handwriting emerged in the late 1980s in the context of mail sorting. *See* Ching-Huei Wang & Sargur Srihari, *A Framework for Object Recognition in a Visually Complex Environment and Its Application to Locating Address Blocks on Mail Pieces*, 2 INT'L J. COMP. VISION 125, 125 (1988); Ofer Matan et al., Handwritten Character Recognition Using Neural Network Architectures (Nov. 1990), http://yann.lecun.com/exdb/publis/pdf/matan-90.pdf.

[141] David John Gagne et al., Day-Ahead Hail Prediction Integrating Machine Learning with Storm-Scale Numerical Weather Models, (2015), https://www.aaai.org/ocs/index.php/IAAI/IAAI15/paper/viewFile/9724/9898.

[142] Richard S. Judson et al., *Estimating Toxicity-Related Biological Pathway Altering Doses for High-Throughput Chemical Risk Assessment*, 24 CHEM. RES. TOXICOLOGY 451, 457–60 (2014); Robert Kavlock et al., *Update on EPA's ToxCast Program: Providing High Throughput Decision Support Tools for Chemical Risk Management*, 25 CHEM. RES. TOXICOLOGY 1287, 1295 (2012); Matthew Martin et al., *Economic Benefits of Using Adaptive Predictive Models of Reproductive Toxicity in the Context of a Tiered Testing Program*, 58 SYS. BIOLOGY REPROD. MED. 3, 4–6 (2012).

drugs.[143] Similarly, the Bureau of Labor Statistics uses machine learning to code survey results about workplace injuries.[144] The U.S. Patent and Trademark Office is exploring how to use machine learning to identify existing literature that may be novelty-defeating "prior art" to patent applications.[145] The Customs and Border Protection uses facial-recognition algorithms to identify people when they arrive in the United States from international airplane flights.[146] The Social Security Administration uses a natural language processing tool based on machine learning that helps flag initial decisions adjudicating disability claims for further quality review.[147]

C. *Impacts and Issues*

The principal advantages of artificial intelligence in the administrative context are similar to those in the private sector: accuracy and efficiency. Machine-learning algorithms can make more accurate forecasts than can aid in governmental decision-making. For example, researchers have shown that if the U.S. EPA were to assign its water pollution inspectors using a machine-learning algorithm in instead of just identifying facilities at random to inspect, they could improve increase the accuracy of finding violations of the Clean Water Act by 600%.[148] A separate analysis of a machine-learning tool that could identify chemicals likely to be toxic showed that it could save the EPA nearly $980,000 for every toxic chemical identified.[149]

In addition to improving the allocation of scarce administrative resources, machine-learning systems may be able eventually help in reducing some of the inevitably biases that are found with unaided human judgment.[150] For example, in

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[143] *Impact Story: Capturing Patient Experience Through Deep Learning*, U.S. FOOD & DRUG ADMIN., https://www.fda.gov/drugs/regulatory-science-action/impact-story-capturing-patient-experience-through-deep-learning (last updated Mar. 5, 2019).

[144] Alex Measure, *Machine Learning: How Bureau of Labor Statistics Did It*, DIGITAL.GOV (July 25, 2019), https://digital.gov/event/2019/07/25/machine-learning-how-bureau-labor-statistics-did-it/.

[145] *See generally* Arti Kaur Rai, *Machine Learning at the Patent Office: Lessons for Patents and Administrative Law* (Duke Law School Public Law & Legal Theory Series, Working Paper No. 2019-37, 2019), http://dx.doi.org/10.2139/ssrn.3393942.

[146] Karlan & Bankman, *supra* note 115 (interview with David Engstrom).

[147] GERALD RAY & GLENN SKLAR, AN OPERATIONAL APPROACH TO ELIMINATING BACKLOGS IN THE SOCIAL SECURITY DISABILITY PROGRAM 31-34 (2009), http://www.crfb.org/sites/default/files/An_Operational_Approach_to_Eliminating_Backlogs_in_the_Social_Security_Disability_Program.pdf; Judge Paul Armstrong, *Artificial Intelligence: From Law Office to Administrative Proceedings*, AM. BAR ASS'N (Feb. 3, 2020), https://www.americanbar.org/groups/judicial/publications/judges_journal/2020/winter/artificial-intelligence--law-office-administrative-proceedings (noting that "the Social Security Administration (SSA) has taken an active role in promoting the use of AI, first in its appeals process and then as an aid in writing and editing its ALJ decisions themselves"); Engstrom & Ho, *supra* note 115, at 9-11.

[148] *See generally* Miyuki Hino, Elinor Benami & Nina Brooks, *Machine Learning for Environmental Monitoring*, 1 NATURE SUSTAINABILITY 583 (2018).

[149] Matthew Martin et al., *Economic Benefits of Using Adaptive Predictive Models of Reproductive Toxicity in the Context of a Tiered Testing Program*, 58 SYS. BIOLOGY REPROD. MED. 3, 4–6 (2012).

[150] *See generally, e.g.*, DANIEL KAHNEMAN, THINKING, FAST AND SLOW (2011).

the context of the Social Security Administration's disability adjudications, some research suggests that human decisions reflect racial disparities that tend to disfavor claimants of color.[151] A study of just a single office within the Social Security Administration found vastly disparate rates of benefits awards, with "judge grant rates in this single location rang[ing] . . . from less than 10 percent being granted to over 90 percent."[152] If machine-learning tools are used as either substitutes for or even just complements to human decision-making, they may be able to reduce inconsistencies and other foibles that permeate human judgment.

On the other hand, the use of machine learning in governmental settings has not escaped controversy. If the underlying data contain biases—particularly as administrative data can derive from human practices and systems that themselves reflect biases and prejudices—then machine learning might simply reify the inequities built into the data.[153]

For example, concerns have arisen about inherent biases built into facial recognition algorithms, given their potential utility for law enforcement agencies.[154] A recent study by the National Institute of Standards and Technology ran millions of photographs obtained from government databases through almost 200 different commercial facial-recognition algorithms.[155]The study found that U.S.-developed algorithms tended to have higher rates of false positives for Asian and African American faces than for white ones (by a factor of between 10 and 100) and more frequent false positives for women than for men.[156]

Moreover, if algorithms rely on underlying data that are limited, or if algorithms are not designed or tested well, they may lead to a false sense of accuracy—perhaps even making decision-making more error-prone. For instance, Indiana's experiment with automating the distribution of public benefits has reportedly resulted in widespread inaccuracies that erroneously deprived many vulnerable people of much-needed public assistance.[157] Furthermore, reliance on

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[151] U.S. GEN. ACCOUNTING OFFICE, GAO/HRD-92-56, SOCIAL SECURITY: RACIAL DIFFERENCES IN DISABILITY DECISIONS WARRANTS FURTHER INVESTIGATION (1992), https://www.gao.gov/assets/160/151781.pdf; Erin Godtland et al., *Racial Disparities in Federal Disability Benefits*, 25 CONTEMP. ECON. POL. 27 (2007).
[152] TRAC, SOCIAL SECURITY AWARDS DEPEND MORE ON JUDGE THAN FACTS: DISPARITIES WITHIN SSA DISABILITY HEARING OFFICES GROW (2011), https://trac.syr.edu/tracreports/ssa/254/.
[153] For recent discussions, compare CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION: HOW BIG DATA INCREASES INEQUALITY AND THREATENS DEMOCRACY (2016), with MICHAEL KEARNS & AARON ROTH, THE ETHICAL ALGORITHM: THE SCIENCE OF SOCIALLY AWARE ALGORITHM DESIGN (2019).
[154] *See* Natasha Singer & Cade Metz, *Many Facial-Recognition Systems Are Biased, Says U.S. Study*, N.Y. TIMES (Dec. 19, 2019), https://www.nytimes.com/2019/12/19/technology/facial-recognition-bias.html.
[155] *NIST Study Evaluates Effects of Race, Age, Sex on Face Recognition Software*, NIST (Dec. 19, 2019), https://www.nist.gov/news-events/news/2019/12/nist-study-evaluates-effects-race-age-sex-face-recognition-software.
[156] *Id.*
[157] *See* VIRGINIA EUBANKS, AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR 39-83 (2018).

large amounts of data gives rise to potential privacy violation and other abuses of power by irresponsible or oppressive governmental actors.[158]

In the governmental setting, the "black box" character of machine-learning algorithms seem to raise particular concerns about transparency and accountability. These concerns have driven increased oversight over the use of algorithms in governmental decisionmaking.[159] The ways that such algorithms optimize outcomes and the solutions they support may not be readily apparent to those who they affect, which has suggested to some observers that either they be avoided in the public sphere or that government officials take extra strides to explain what these algorithms do.[160]

For example, a school district in Boston worked with researchers at the Massachusetts Institute of Technology to use a machine-learning algorithm to help redesign student bus schedules in a way that would have saved the district up to $15 million in annual expenses and produced schedules that were healthier for students, better for the environment, and more equitable for minority students.[161] But the bus schedule's "overhaul was introduced with insufficient explanation or opportunity for citizen interaction with the model," resulting in a "public pushback [that] was strong and swift."[162] The school district eventually dropped the proposed scheduling changes.

In Houston, a school district ended up in court after relying on a complex algorithm—albeit not a machine-learning one—to rate teachers' performance and justify the dismissal of teachers who rated poorly.[163] The district relied on a private consulting firm to develop and run the algorithm, but the firm considered its "algorithms and software as trade secrets, refusing to divulge them to either [the district] or the teachers themselves."[164] The teachers' union and several teachers

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[158] *See, e.g.,* Rashida Richardson, Jason M. Schultz & Kate Crawford, *Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, And Justice*, 94 N.Y.U. L. REV. 192, 192 (2019) (raising concerns about the use of "dirty data" from corrupt, racially biased, or unlawful police practices in algorithmic tools to support predictive policing, which can further perpetuate the biases and misbehavior inherent in the data); Shibani Mahtani, *Chicago Police Take a Page From "Minority Report*," WALL ST. J. (May 12, 2017), https://www.wsj.com/articles/chicago-police-take-a-page-from-minority-report-1494581400; Ali Winston & Ingrid Burrington, *A Pioneer in Predictive Policing Is Starting a Troubling New Project*, THE VERGE (Apr. 27, 2018), https://www.theverge.com/2018/4/26/17285058/predictive-policing-predpol-pentagon-ai-racial-bias.

[159] For instance, New York City was the first in the country to set up a task force to oversee the use of automated decision systems by city agencies. *See generally* NYC AUTOMATED DECISION SYSTEMS TASK FORCE, NEW YORK CITY AUTOMATED DECISION SYSTEMS TASK FORCE REPORT (2019), https://www1.nyc.gov/assets/adstaskforce/downloads/pdf/ADS-Report-11192019.pdf.

[160] *See* AI NOW INST., AI NOW 2019 REPORT (2019), https://ainowinstitute.org/AI_Now_2019_Report.pdf (flagging a variety of concerns about the "black box" nature of algorithms and the potential for harm and abuse if they are used by government agencies without fully accounting for built-in biases).

[161] ELLEN GOODMAN, THE CHALLENGE OF EQUITABLE ALGORITHMIC CHANGE (2019), https://www.theregreview.org/wp-content/uploads/2019/02/Goodman-The-Challenge-of-Equitable-Algorithmic-Change.pdf.

[162] *Id*. at 3, 7.

[163] Hous. Fed'n of Teachers, Local 2415 v. Hous. Indep. Sch. Dist., 251 F. Supp. 3d 1168, 1171 (S.D. Tex. 2017); *see also* Coglianese & Lehr, *supra* note 1, at 37-38.

[164] *Id.* at 1176-77.

took the district to court, arguing that the algorithm deprived them of procedural due process.[165] They argued that, without "access to the computer algorithms and data necessary to verify the accuracy of their scores," the district deprived them of their constitutional rights. The trial court issued only an interim decision, ruling that the procedural due process claim could possibly have merit and the teachers were entitled to take their case to a jury. The court held that "without access to . . . proprietary information—the value-added equations, computer source codes, decision rules, and assumptions—[the teachers'] scores will remain a mysterious 'black box,' impervious to challenge."[166] Although the court recognized that the consulting firm may well have been in its rights to keep its algorithms secret, it held that a jury could consider whether "a policy of making high stakes employment decisions based on secret algorithms [is] incompatible with minimum due process."[167] Of course, the preliminary nature of the trial court's decision cannot rule out the possibility that, had the matter gone to a jury, the school officials might have been able to put forth additional evidence that could have satisfied the teachers' due process rights while still protecting the firm's trade secrets.

Other cases have in recent years have raised due process concerns over states' use of non-learning algorithms in making decisions to reduce individuals' Medicaid benefits. In Idaho, lawyers acting on behalf of developmentally challenged adults filed suit against the state over reductions in Medicaid payments for long-term institutional services.[168] The state relied on a proprietary algorithm used in setting individual budgets that were then used in calculating Medicaid benefits.[169] Idaho initially argued that the methodology used by the non-learning algorithm was a "trade secret" and refused to disclose it to the plaintiffs unless they signed a confidentiality agreement.[170] The court rejected this assertion and the parties ultimately stipulated to a preliminary injunction under which Idaho agreed to make details about its budget calculation tool available to participants in the program upon request.[171]

The West Virginia Department of Health and Human Resources was also sued over its use of a non-learning algorithm that determined Medicaid recipients' budgets for the care they needed.[172] When the algorithmically determined budgets

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[165] *Id.* at 1171-73.
[166] *Id.* at 1179.
[167] *Id.* at 1179-80.
[168] *See generally* K.W. v. Armstrong, 298 F.R.D. 479, 494 (D. Idaho Mar. 25, 2014); Schultz v. Armstrong, No. 3:12-CV-00058-BLW, 2012 WL 3201223 (D. Idaho Aug. 2, 2012). For a discussion of this litigation, see Bloch-Wehba, *supra* note 125 (manuscript, at 15-16, 35).
[169] *See* Bloch-Welba, *supra* note 125 (manuscript at 15-16).
[170] *Id.*
[171] *Id.* In subsequent litigation, the plaintiffs moved to certify a class of similarly situated individuals; the court granted the motion and expanded the injunction to reach the entire class. K.W. v. Armstrong, 298 F.R.D. 479, 494 (D. Idaho Mar. 25, 2014). On appeal, the Ninth Circuit affirmed, holding that the district court did not abuse its discretion in finding that the notices informing the plaintiffs of the reduction in their benefits as a result of the algorithm's determinations failed to lay out properly the agency's rationale for the reductions. K.W. *ex rel.* D.W. v. Armstrong, 789 F.3d 962, 971-74, 976 (9th Cir. 2015).
[172] Michael T. v. Bowling, No. 2:15-cv-09655, 2016 WL 4870284, at *1-4 (S.D. W. Va. Sept. 13, 2016), *modified sub nom.* Michael T. v. Crouch, 2018 WL 1513295 (S.D. W. Va. Mar. 26, 2018).

resulted in significantly reduced benefits for the plaintiffs, they filed a class-action suit alleging violations of due process and seeking to enjoin the use of the algorithm because they had no way of knowing the criteria it relied on to determine their budgets and they therefore lacked meaningful opportunities to contest its determinations.[173] The court agreed and issued a preliminary injunction prohibiting the algorithm's use, since the agency failed to disclose the algorithm's overarching methodology, the variables it used, or how it weighted these variables.[174] The court lifted its injunction after West Virginia developed and made publicly available an alternative system which relied on matrices and allowed recipients to contest the accuracy of the variables and the overall use of the matrix.[175]

It seems clear from the Idaho and West Virginia cases that government agencies will be on the thinnest ground when they disclose absolutely nothing about the algorithms they use. But both of these cases involved algorithms made up of a limited number of fully known variables that had been assigned specific weights.[176] It remains to be seen what courts will demand that states disclose when they rely on complex, machine-learning algorithms that are not so intuitively explainable. Given that due process calls for balancing,[177] it may be that the Houston school district case comes the closest to the likely outcome in procedural due process challenges to the administrative use of machine-learning algorithms—where the ultimate judgment about the due process calculus and the balancing of interests at stake will be one for a jury to make.[178]

In addition to lawsuits raising procedural due process claims, administrative agencies that rely on machine-learning algorithms are likely to face claims of algorithmic bias based on federal statutes, such as Title VI of the Civil Rights Act of 1964, which prevents state and local governments that receive federal financial assistance from engaging in practices that have disparate impacts on protected classes. The due process and equal protection clauses of the Constitution's Fourteenth and Fifth Amendments also prevent state and federal governments, respectively, from engaging in intentionally discriminatory practices. If agencies are not careful, they could certainly use machine-learning tools in ways that offend existing principles of constitutional or statutory law.[179] However, the responsible

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[173] *Id.* at *4, *7-9.
[174] *Id.* at *10-12, *15.
[175] *Crouch*, 2018 WL 1513295, at *6-13; *see also* Bloch-Wehba, *supra* note 125 (manuscript at 13-15).
[176] The cases discussed in Part I of this Article addressing judicial use of algorithms are also obviously relevant to the administrative use of algorithms. However, just as here, none of those cases addressed any truly *machine-learning* algorithms.
[177] Under current federal law, courts are expected to determine what procedural due process requires by balancing three factors: the interests of the private individual; the risk of erroneous decisions; and the interests of the government. *See generally* Mathews v. Eldridge, 424 U.S. 319 (1976). For elaboration in the context of algorithmic tools, see Coglianese & Lehr, *supra* note 1, at 40-42.
[178] As noted, the algorithm at the center of the Houston case was also not a machine-learning one.
[179] *Cf.* Mulligan & Bamberger, *supra* note 45, at 782-83, 808-29 (proposing administrative law "as the framework to guide the adoption of machine learning governance" in light of the fact that current machine learning systems often incorporate policy choices that fail to comply with the general prohibition on arbitrary and capricious agency actions). *See generally* Michael L. Rich, *Machine Learning, Automated Suspicion Algorithms, and the Fourth Amendment*, 164 U. PA. L. REV. 871

use of machine learning can probably be readily accommodated under existing principles of U.S. law.[180]

CONCLUSION

Although the day when a judge's role is fully supplanted by an algorithm is surely still far into the future, if it should ever completely come,[181] the building blocks that could eventually give rise to a world of increased use of artificial intelligence by governmental entities have started to manifest themselves in state and federal legal systems across the United States. The widespread adoption of risk assessment tools in criminal cases in courts at every level of government appears to reflect an increasing comfort in allowing algorithms to inform decisions. Increasing digitization of court records could potentially provide judicial managers with troves of data for artificial intelligence programs that could analyze and possibly even facilitate future automated adjudication. The growing adoption of online dispute resolution by both the private organizations and the courts could also eventually make the public more comfortable with fully computerized and automated adjudication. The opportunities for successful application of artificial intelligence seem even greater in administrative agencies, and they are already starting to rely on machine learning tools to inform enforcement decisions, allocate social services, and manage programs.

Overall, these tools appear to have great promise. As with any tool, of course, if they are not used with care, they may give rise to further problems which may generate conflict and litigation. Public concerns have already arisen over the use of algorithms in predictive policing and in the criminal justice system more generally. The few court cases decided to date do not suggest that the judiciary will ultimately disapprove of responsibly designed and implemented machine-learning tools—and it is certainly beyond the limits of any kind of intelligence, human or artificial, to forecast with precision what the future will hold for governmental use of machine learning in the United States. Yet with the continued reliance on machine learning in other spheres of life, the public acceptability of, if not demand for, its use in the governmental sector may only increase.

(2016) (arguing that using algorithms in police investigations could raise significant Fourth Amendment concerns that have yet to be examined by courts).

[180] Coglianese & Lehr, *supra* note 1; Coglianese & Lehr, *supra* note 13.

[181] Dave Orr and Colin Rule, Artificial Intelligence and the Future of Online Dispute Resolution 10 (unpublished manuscript), http://www.newhandshake.org/SCU/ai.pdf ("We are still a long way away from giving an AI Lexis-Nexis access and then asking it to serve on the Supreme Court.").